2017 Short-term Peak Forecast and Weather Normalization Overview

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DAWG Demand Forecasting Pup
2017 IEPR Revised Demand Forecast
Related Methodology Issues

California Energy Commission
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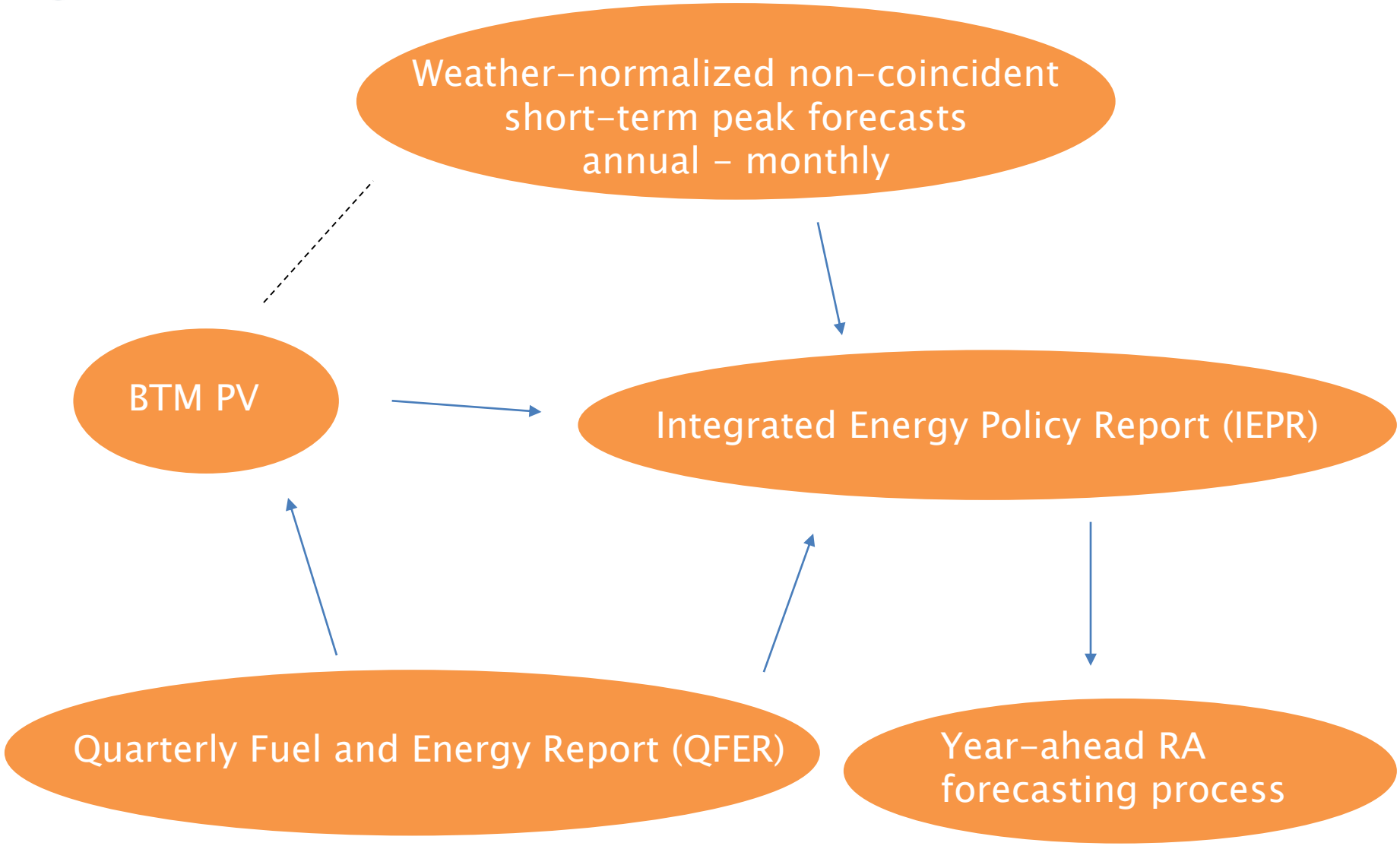
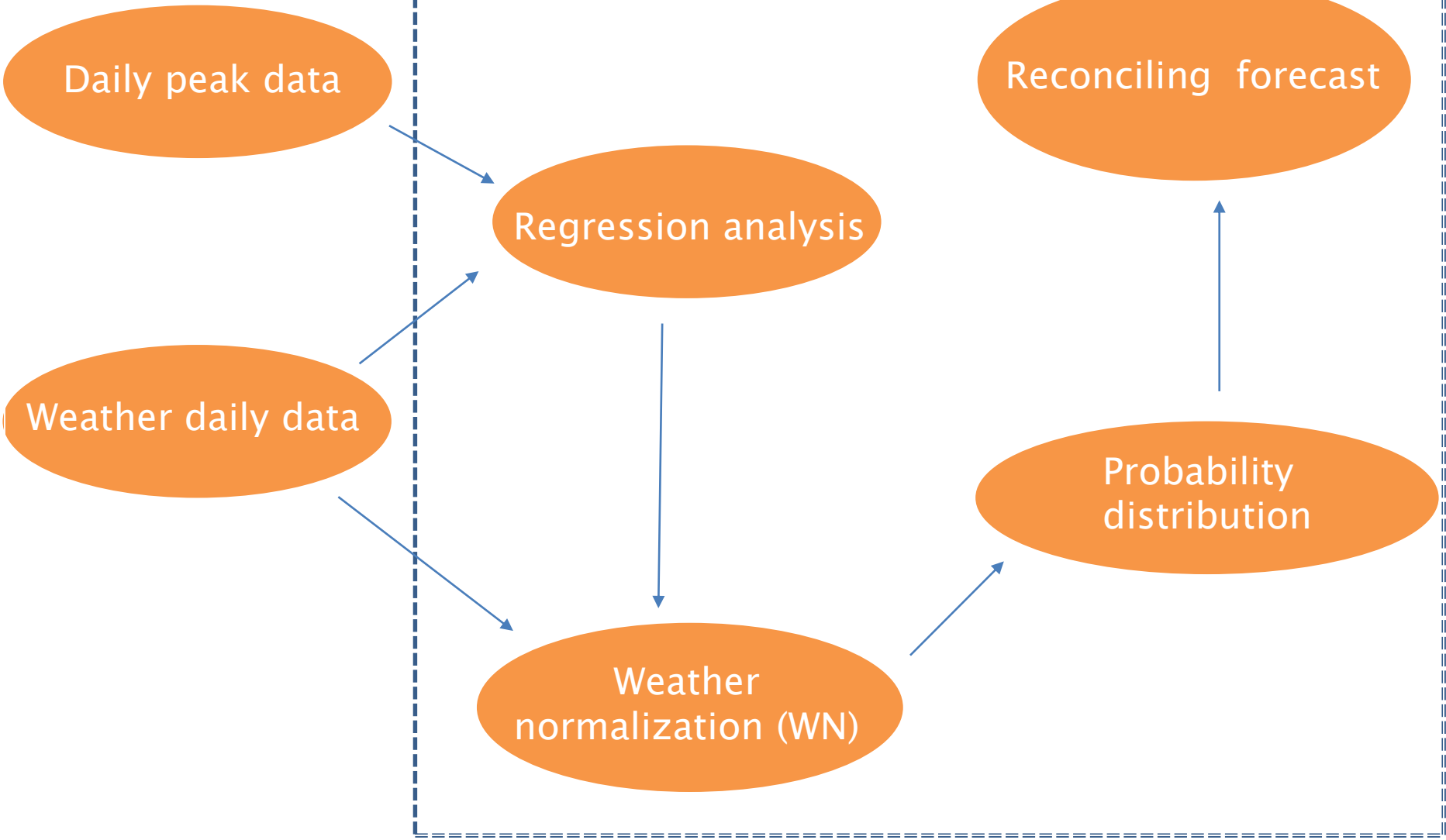
Weather-normalized non-coincident short-term peak forecasts and IEPR



Process to estimate weather-normalized non-coincident short-term peak forecasts



The Challenge

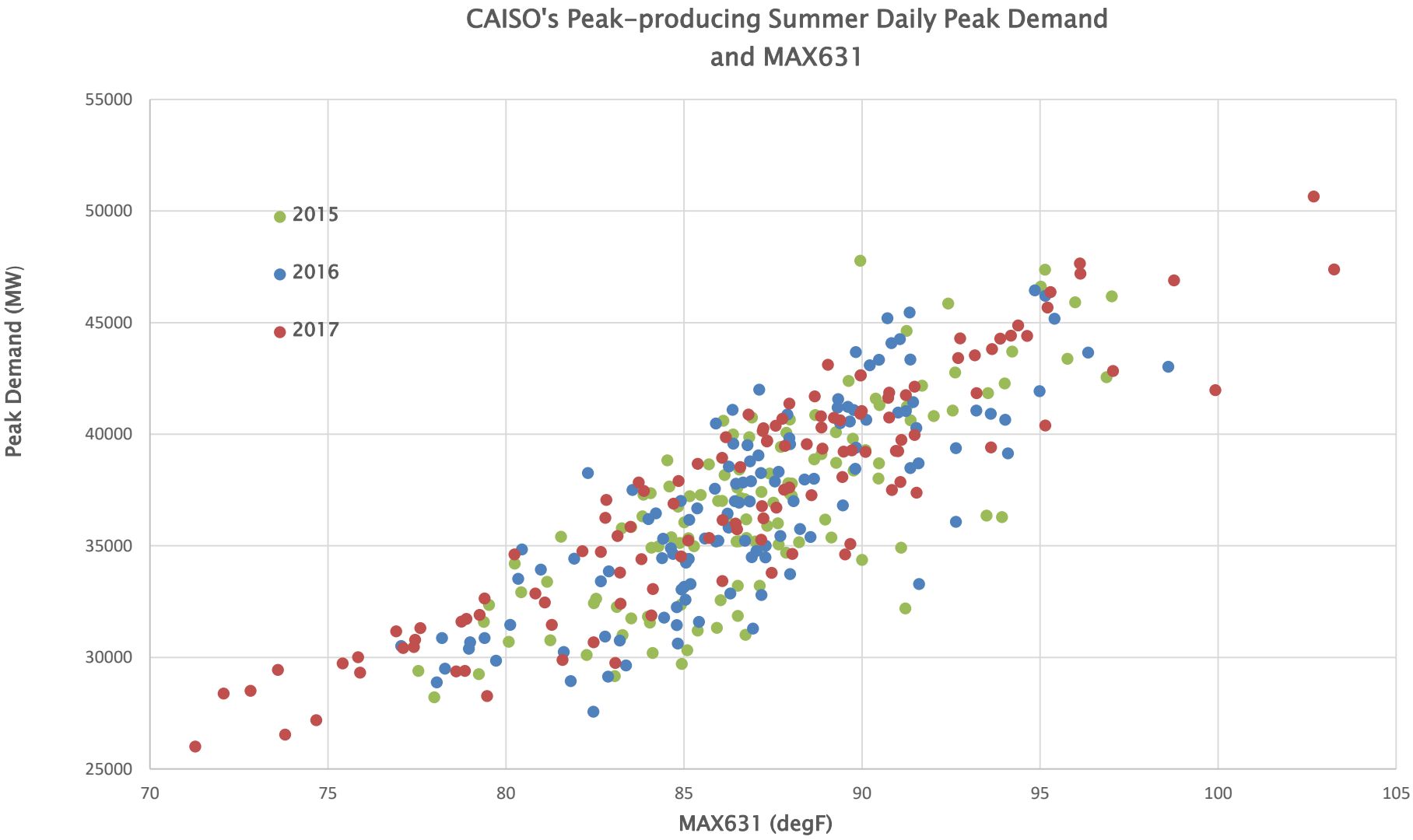
- How to better capture summer weather-sensitivity peak loads and weather patterns across TACs and time
  - temperature lagged effects
  - temperature non-linear effects
  - time trend effects
  - calendar effects

The Data

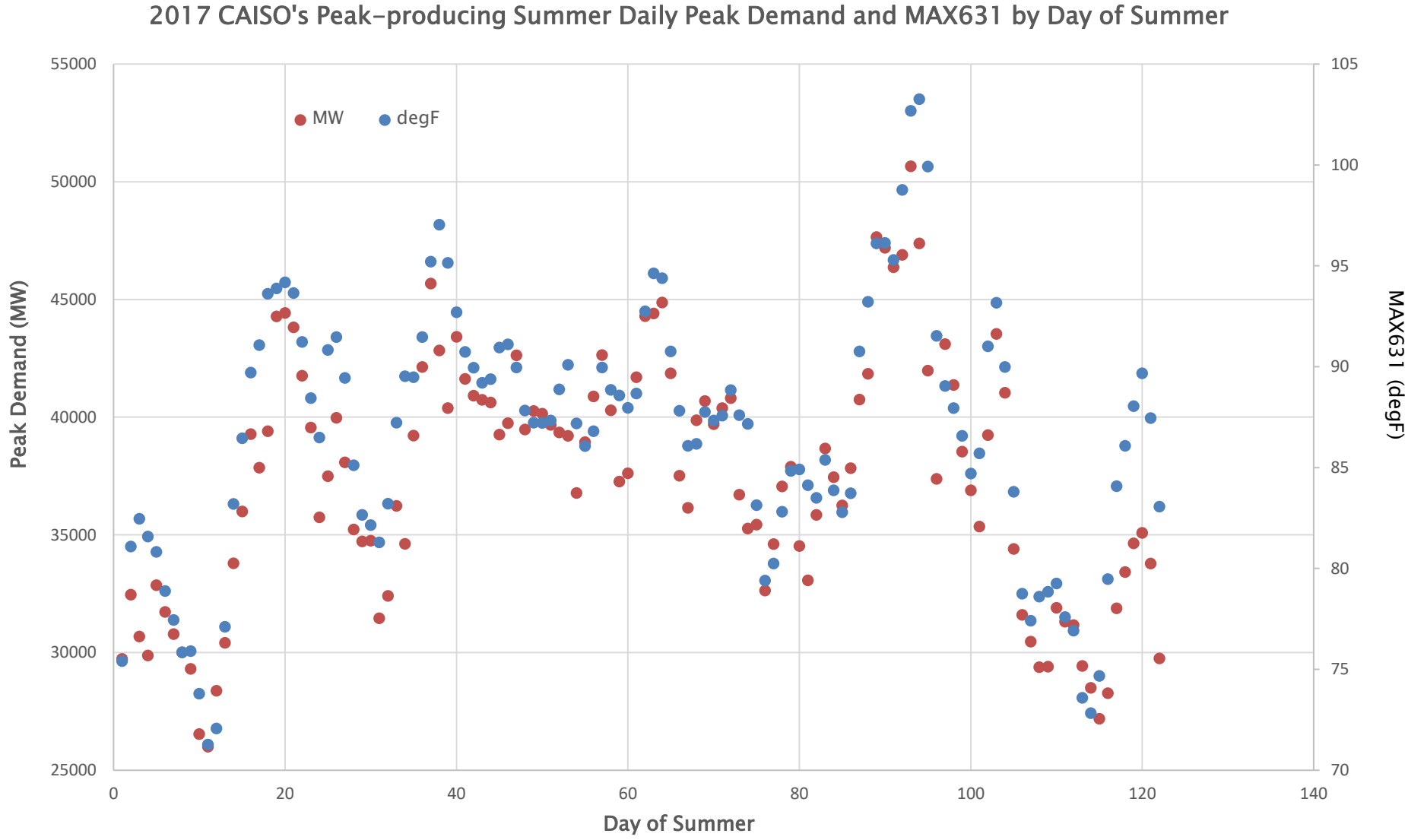
- Daily peak data – 3-years (2015 to 2017) hourly load data from CAISO's EMS by TAC
  - embedded hourly demand response (IOU's)
  - June 1th to September 30th, 122 peak-producing summer days per year, 488 days

- Daily weather data – 30-years (1988 to 2017) summer weather data (max and min), 3660 days
  - weather stations weighted by stations (AC units/saturation) and aggregated by TAC

The Data


CAISO's Peak-producing Summer Daily Peak Demand and MAX631
Peak Demand (MW)
55000
50000
45000
40000
35000
30000
25000
2015
2016
2017
70
75
80
85
90
95
100
105
MAX631 (degF)

The Data


2017 CAISO's Peak-producing Summer Daily Peak Demand and MAX631 by Day of Summer
MW
degF
Peak Demand (MW)
MAX631 (degF)
Day of Summer
55000
50000
45000
40000
35000
30000
25000
105
100
95
90
85
80
75
70
0
20
40
60
80
100
120
140

Frequency of Summer Peak-Hours over time

TAC	Year	Hour 17	Hour 18	Hour 19	Hour 20	Hour 21	Hour 22
CAISO	2015	49	54	3	1	6	
	2016	29	68	8	8	9	
	2017	18	66	15	14	9	
PGE	2015	11	61	32	8	6	
	2016	1	36	63	11	7	4
	2017	3	23	70	18	5	3
SCE	2015	90	14			6	
	2016	68	33		4	9	
	2017	67	28	1	11	6	
SDGE	2015	45	29		6	28	
	2016	11	52	5	18	34	
	2017	6	50	13	19	31	

Regression analysis

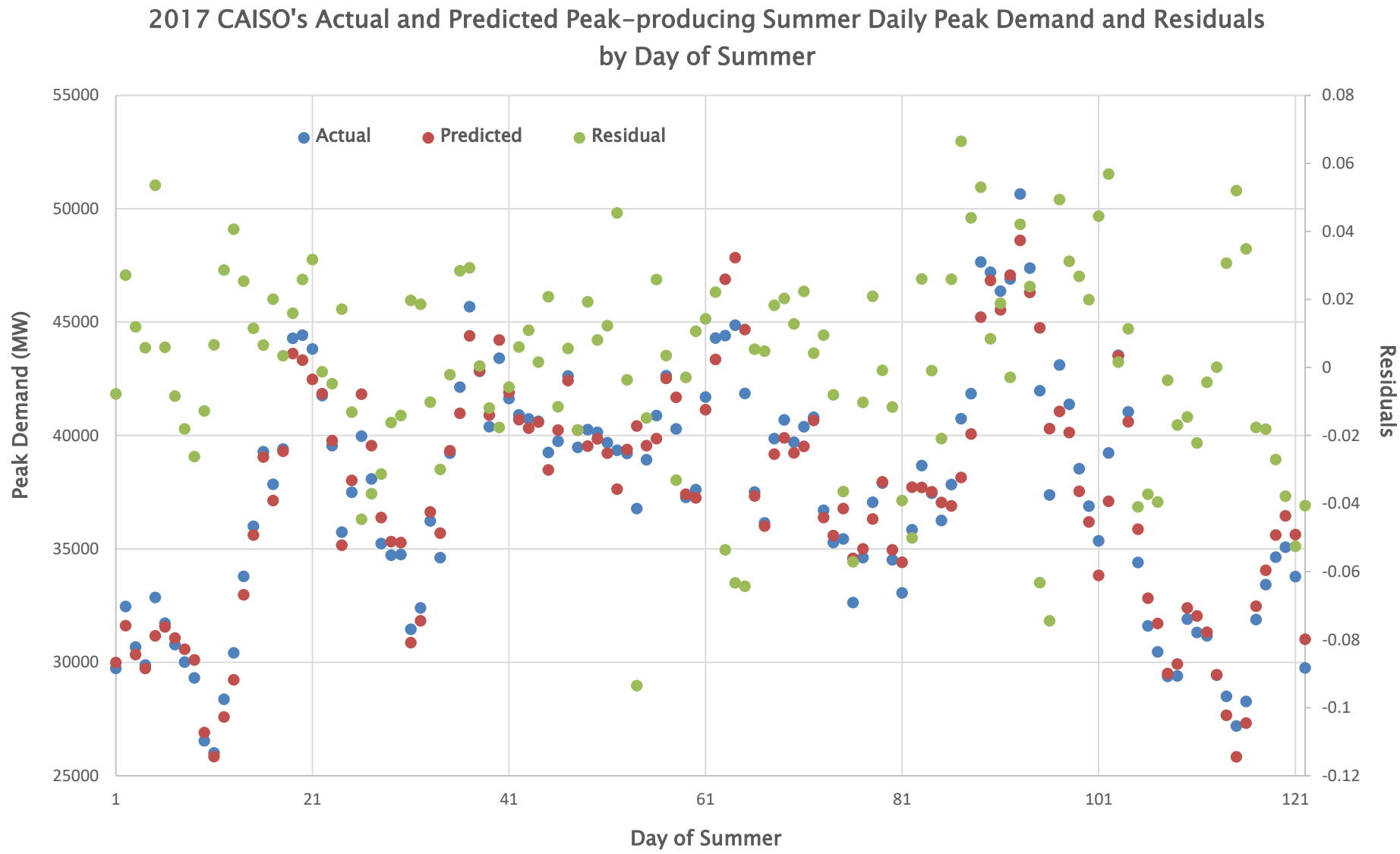
- Selected variables – best simulation accuracy by regression model refit (bootstrap) and Bayes factors
  - logarithm peak-producing daily peak loads (MW)
  - temperature lagged and non-linear effects
    - 3-day weighted moving average of max
    - max631 – restricted cubic splines
  - calendar time-trend effects (as dummies)
    - day of the week (weekday vs weekend)
    - day of summer – restricted cubic splines
    - holiday, monthly, and yearly binary variables

Regression analysis

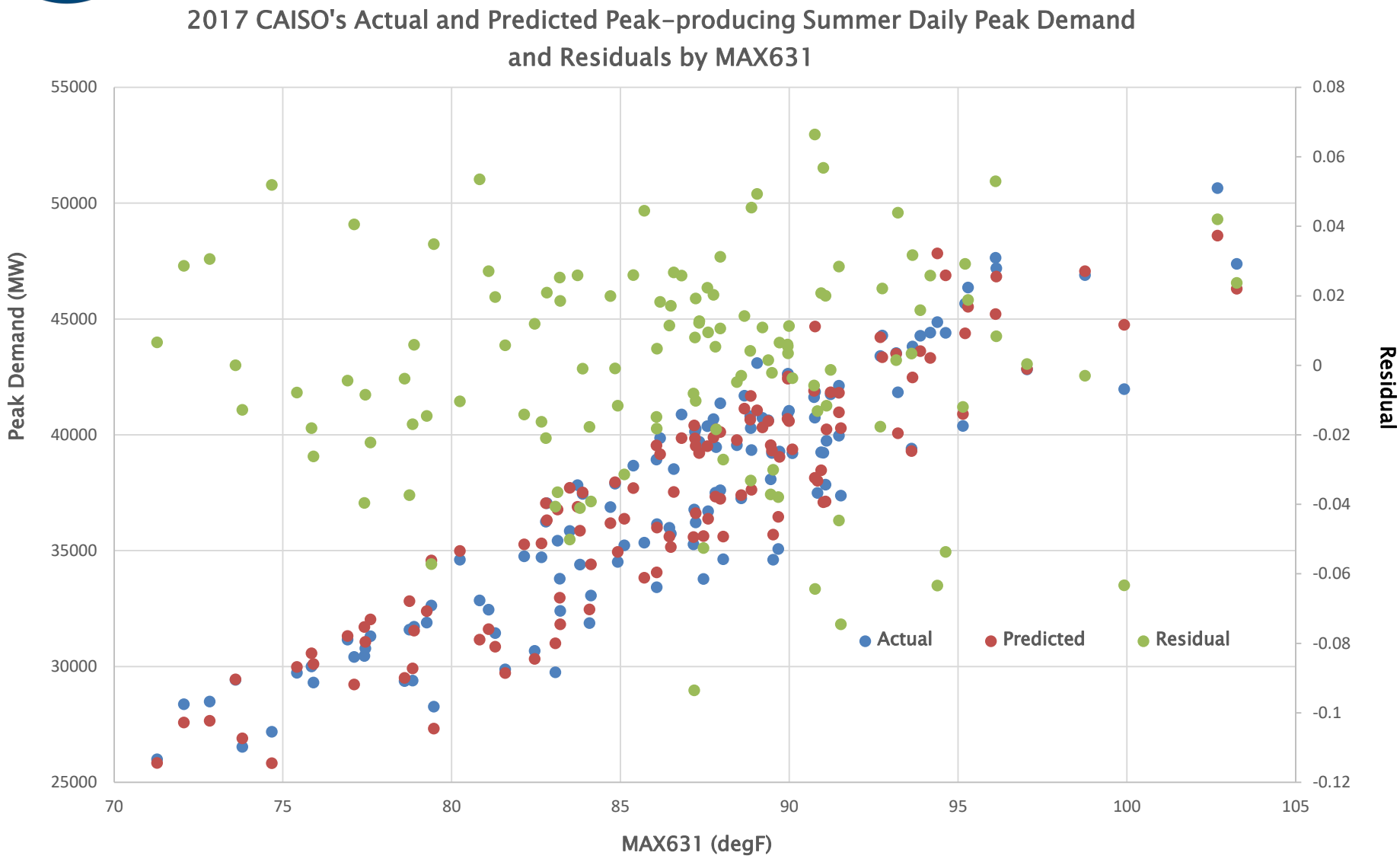
- A time-series semi-parametric additive model with first-order serial correlated errors
  - estimation techniques – ML and Bayesian
  - validation by temperature and residual bootstrapping
    - Selected results of regression analysis

TAC	Percentage increase in MW per 5 additional max631s
CAISO	8.33
PGE	10.14
SCE	11.63
SDGE	10.27

Regression analysis



Regression analysis



Probability distribution

- Better understand and quantify weather patterns, diversity, and uncertainty
- Actual historical weather through weather-related regression coefficients (122 days / 30 years / 3660 points)
  - days treated as weekdays, as peak-producing days
- most likely WN non-coincident peak load for each TAC
  - median from annual peak load simulated probability distribution (30 points)
  - 90^{th} / 50^{th} – how much higher the top 10% peak loads are to the median

Probability distribution simulation

- **Results of Probability Distribution Simulation by TAC**

TAC	Source	Peak Load MW	Peak date	MAX631 at the time	Rank of Peak Load	Rank of MAX631	WN factor
CAISO	Actual	50654	01Sep17	102.69	94	95	
	50th WN	44556		94.73	50	50	.880
PGE	Actual	21846	01Sep17	102.20	88	91	
	50th WN	20431		97.41	50	52	.935
SCE	Actual	24654	01Sep17	104.44	97	94	
	50th WN	21070		97.51	50	52	.855
SDGE	Actual	4585	01Sep17	96.57	91	68	
	50th WN	4167		94.45	50	52	.909

Reconciling forecast

- TAC forecasts need to add up to CAISO level as the observed peak load time series – EMS?
- CAISO forecast vs. PGE, SCE, and SDGE TAC forecasts
  - adding up independent forecasts at TAC level to CAISO level – bottom-up
  - allocating CAISO forecast to TACs based on historical forecast errors and weights – top-down
  - something in-between to adjust forecasts
    - Bayesian model averaging with varying time weights
- Temporal / frequency reconciliation

And that's it